Hyperspectral Remote Sensing: Dimensional Reduction and End member Extraction

Muhammad Ahmad, Sungyoung Lee, Ihsan Ul Haq, Qaisar Mushtaq

***Abstract*—In this work, we present an algorithm to overcome the computational complexity of hyperspectral (HS) image data to detect multiple targets/endmembers accurately and efficiently by reducing time and complexity. In order to overcome the computational complexity standard deviation and chi square distance metric methods are considered. The number of endmembers is estimated by unbiased iterative correlation method. Hyperspectral remote sensing is widely used in real time applications such as; Surveillance, Mineralogy, Physics and Agriculture.**

***Index Terms*—Hyperspectral data, chi square, correlation, unbiased, Mat lab**

I. INTRODUCTION

Hyperspectral remote sensing has been used for increasing knowledge and perception of the earth's surface. Hyperspectral imaging is concerned with capacity, examination, and analysis of the spectra acquired from a given sensor in a short, medium or long distance by an airborne or satellite [1]. NASA's Jet Propulsion Laboratory (JPL) began a revolt in remote sensing by developing new instruments such as the airborne imaging spectrometer. This concept of hyperspectral imagery was beginning in the 1980's by A. F. H. Goetz and his colleagues at NASA's [1]. This system was used more than 200 spectral bands and able to cover the wavelength region from 0.4-2.5µm at a nominal spectral resolution of 10nm [2, 3]. Hyperspectral remote sensors concurrently collect image data in dozens or hundreds slight and neighboring spectral bands over wavelength that can range from the ultraviolet to the thermal infra-red at resolution of fine 10nm.

This unique spectral resolution has opened the door to a series of civilian and military applications among which we refer to; land use, agriculture assessment, ecological and environmental monitoring, ground-cover classification, mineral exploitation, change detection, man-made materials identification and detection, target activities, and surveillance. Underlying all these applications is the fact that all substance's scatter electromagnetic energy, at specific wavelengths, in distinctive patterns related to their molecular composition.

Data reduction is a consequence of the fact that the number of end members presents in the scene is usually much smaller than the number of bands. High dimensional data contains the significant amount of features information including hyperspectral data with redundant information in terms of spectral signatures. Therefore, reducing the dimensionality without missing important information or objects of interest is very important issue. Dimensional reduction is categorized in two ways; (1) Feature extraction is done by mapping the correlation of high dimensional data onto the uncorrelated low dimensional data, (2) Feature selection techniques do not alter the original representation of the variables, but merely select a subset of them, thus there is no need of any transformation while selecting a subset of features for dimensional reduction, but we have to concentrate on selecting features among the existing features [4].

Hyperspectral data unmixing usually carried out by two steps; (1) End member detection is estimating the spectral signatures of different end members present in the data, and (2) Inversion is to find the abundance fractions of each end member. The spectrum of the target and the spectra of the background may also be used for end member detection to the observed mixed pixel spectrum [5].

There are many algorithms to unmix hyperspectral data; most of algorithms assume that pure pixel is present in the data like independent component analysis (ICA) [6], Vertex Component Analysis (VCA) [7], Pixel Purity Index (PPI) [8], N-FINDR [9], Gift Wrapping Algorithm, Principal Component Analysis (PCA), Multi End Members Spatial Mixture Analysis (MESMA) based on the SMA algorithm.

Due to the low resolution of hyperspectral sensor, more than one distinct substance may exist in a hyperspectral image pixel. Measured spectral is a composite of the individual spectrum of each material that is exist in that pixel [10]. Mixed pixels can also be due to a homogeneous mixture of distinct materials. This kind of mixed pixel is independent of sensor resolution [10]. Unmixing of hyperspectral image pixel is the decomposition estimation of the pixel spectrum into a collection of constituent spectra called endmember spectral signatures, and their corresponding abundance fractions [10, 11]. Spectral and spatial resolution can be changed with unmixing [12, 13]. Multispectral and hyperspectral image analysis can be classified as follows [14, 15]: detect known or unknown objects or materials [16, 17]; classification [15, 16, 17]; estimate the materials and the respective area fractions that they occupy within a pixel [18, 19]. The spectrum of the target and the spectrum or spectra of the background may also be used for sub pixel/endmember detection to the observed mixed pixel spectrum [20, 21].

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End-members derivation methods can be grouped into two main classes. First type of algorithm assume that end-member exist in the image either in pure pixel or in mixed pixel. The algorithms which assume pure pixel are present in image data; use the selection of n-dimensional scatter plot method and the convex cone method [22, 23]. Second type of algorithm derives the spectra of end-members analytically [12, 13, 24, 25, 26].

Two models are widely used for modeling mixed pixels: linear mixture model [27, 28, 29] and non-linear mixture model [30]. Mostly linear mixing model (LMM) has been used for source separation in mixing activities [31, 32]. In LMM modeling, it is assumed that the observed pixel spectrum is the linear combination of a small number of unique and distinct constituent deterministic spectral signatures (endmembers/ targets). The LMM for hyperspectral mixed pixel can be expressed in mathematics in the following way [33].

$$X = \sum_{k=1}^{K} a_k * s_k + W = Sa + W \qquad (1)$$

Where $S = [s_1\ s_2\ \ldots.\ s_K]$ are the K end member spectra (targets). These target spectra are assumed to be linearly independent. $a = [a_1\ a_2\ \ldots.\ a_K]^T$ are the corresponding abundance fractions, and W is an additive noise vector or can be interpreted as measurement error or a model error. If L the spectra bands then X is an L * 1 column pixel vector and S is a target signatures matrix of size L * K.

If the endmember spectra are randomly and independently drawn from multivariate normal distributions, then stochastic mixing model [34] is considered. The choice of a pixel composition assumption (pure or mixed pixel), the selection of a model to account for spectral variability (subspace or probability distribution), and the selection of a mixing procedure leads to different types of target detection algorithms. The detection problem is typically formulated as a binary hypothesis test with two competing Hypotheses: background only (H0) or target and background (H1). Since the two hypotheses contain unknown parameters (for example, covariance matrix of the background) that have to be estimated from the data, the detector has to be adaptive, and it is usually designed using the generalized likelihood ratio test approach [31]. Most detection algorithms for full pixel and sub pixel (endmember) targets have been obtained by describing spectral variability using the multivariate normal distribution or a subspace model. Mixed pixels are usually modeled using the LMM. A target detection algorithm based on the stochastic mixing model, known as finite target matched filter, is discussed in [35] and [34].

In this paper a linear mixture model is used shown in equation (1). To illustrate this, assume that a linear combination of $S = [s_1\ s_2\ \ldots.\ s_K]$, Signatures and their corresponding abundance fractions $a = [a_1\ a_2\ \ldots.\ a_K]^T$, (i = 1, 2… K), Where K is the total number of targets and L is the total number of bands. Thus $\bar{X}_i = \bar{S}\vec{a} + \bar{W}$, we assume that the signatures of the $i-th$ end member can be written as $\bar{M}_i = \frac{1}{P}\sum_{k=1}^{P}\left[c_k\rho_{k_i}\right]^T$, and also we assume that the sensor radiation pattern is ideal. So the $k-th$ output of the channel at a given pixel is defined as $R_k = c_k\left[\frac{1}{K}\sum_{i=1}^{K}\left\{\rho_{k_i}s_i + d_{k_i} + n_{k_i}\right\}\right]$, where c and d are directly proportional to a and b with wave length λ respectively and the receiver electronic noise and the Poisson signal noise is defined as n at the $i-th$ channel. Since the values of a and b are depend on the sensor and sun light directions, atmosphere composition, the topology and on the scene materials and configurations. Where ρ_{k_i} denotes the reflectance of the end member i at the wave length λ_K and $\vec{s}_K$ Shows the abundance fractions of the end member I at the considered pixel and also here p is denotes the number of end members. It is still linear and accounts for illumination fluctuations, signatures variability, and sensor noise.

II. CHALINGE IN HYPERSPECTRAL IMAGERY

The accuracy increases as the increment in spectral bands of hyperspectral imagery. Due to data redundancy, the convergence stability causes accurse. Furthermore, the variation due to noise in redundant data propagate trough a classification model. Since to over-come and sought-out the problems of computational requirements for processing large data might be prohibitive and the data subsets may be used. Since the hyperspectral imagery provides the vast amount of information about images or scene. To over-come the computational problems and for obtaining the good results, it is necessary to reduce the dimensions of the hyperspectral data. Following are some challenges of hyperspectral image analysis:

- Data storage and transmitting the date due to huge data volume.
- Data redundancy challenge. Information of all the bands may not un-correlated.
- Processing time for both supervised and un-supervised techniques.
- Hughes phenomenon is observed in hyperspectral imagery data classification because of limited training data and ratio of the training pixels to the number of bands is small.

Increments in used features would not always increase the end member detection, unmixing, and classification accuracy. So, this is the fact that we need more samples in accurately specifying the decision boundary for classification for hyperspectral data.

III. APPLICATIONS

Hyperspectral remote sensing has been used in a large array of real life applications, although initially it was developed for mining and geology. The capability of hyperspectral imaging to classify various minerals makes it ideal for the mining and oil industries where it can be used to discover ore and oil [36, 37]. It has now spread into fields as wide spread as ecology and surveillance as well as historical manuscripts research such as; the imaging of the Archimedes palimpsest.

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This know-how has persistently become more on hand to the public and has been used in a broad range of ways. Organizations such a NASA and USGS have catalogues of various minerals and their spectral signatures. They and have made them available online to be used by the research community, those data are categorized as following:

- Surveillance
- Mineralogy
- Physics
- Agriculture

IV. POBLEM STATEMENT

Our main consideration and interest is to enhance the results of hyperspectral data dimensional reduction and end member detection accurately by using the statistical parameters, suchas; mean absolute deviation, chi square distance, and correlation.

The emergence of image data with large number of spectral bands has presented image processing and interpretation challenges yet they not experienced with hyperspectral imagery data set. There is a need to develop the detection, unmixing and classification methods to utilize the amount of information and reparability that hyperspectral images data offers while simultaneously avoiding the difficulties inherent in hyperspectral space. Since there is no doubt that more of information is contains in hundreds of narrow and adjacent bands of hyperspectral images data but some of them bands overlap the information or some of bands are un correlated.

V. FORMULATION

Assume that $\overline{X} = [\vec{r}_1, \vec{r}_2, \vec{r}_3 \ldots \vec{r}_N] = \overline{S}\vec{a} + \overline{W}$ is an L x N matrix where L is the total number of bands.

Suppose that we have $\{B_i\}_{i=1}^{L}$band images in hyperspectral image data, if each band image is of size M × N and B_i be the mean of the i_{th} band image then mean absolute deviation $(MAD_{\tilde{\chi}})$ for i_{th} band is calculated as,

$$D_i = \frac{1}{MN}\sum_{i}^{MN}\left|b_i - \widetilde{B}_i\right| \qquad (2)$$

For the set of observations$\sum_{i=1}^{L}\overline{X}$, the K-means clustering method partitions the n observations into k sets ($k < n$), $\overline{C} = \{\vec{C}_1, \vec{C}_2, \vec{C}_3, \ldots, \vec{C}_k\}$, minimizing the sum of squares with-in clusters as,

$$\text{argMin}_S \sum_{i=1}^{k}\sum_{x_j \in C_i}\left\|x_j - \tilde{\mu}_i\right\|^2 \qquad (3)$$

Where $\tilde{\mu}_i$is the median of points in clusterC_i and n_k is the number of points in C_k.For an m x n data matrix $\sum_{i=1}^{L}\overline{X}$ the distance between the vector $x_r$and x_s is defined as,

$$C\_D_{r;s} = \sqrt{\sum_{i=1}^{N}\left[\left(\frac{x_r}{S_{x_r}} - \frac{x_s}{S_{x_s}}\right)_i^2 D^{-1}\left(\frac{x_r}{S_{x_r}} - \frac{x_s}{S_{x_s}}\right)_i^2\right]} \qquad (4)$$

$$C\_D_{r;s} = \sqrt{\sum_{i=1}^{N}\left(\frac{1}{S_{x_r} * S_{x_s}}\right)^2\left[(x_r - x_s)_i^2 D^{-1}(x_r - x_s)_i^2\right]} \qquad (5)$$

$$C\_D_{r;s} = \left(R_{x_{r,s}}\right)^2\sqrt{\sum_{i=1}^{N}\left[(x_r - x_s)_i^2 D^{-1}(x_r - x_s)_i^2\right]} \qquad (6)$$

Where S_{x_r} is the standard deviation of the r^{th} variable, similarly for S_{x_s}. Notice that we need not subtract the r^{th}mean from x_r and x_s because they will just cancel out in the differencing, $R_{x_{r,s}} = \frac{1}{S_{x_r} * S_{x_s}}$ the inverse of the r^{th}&s^{th} variance. Hence those bands are selected which carried the maximum mutual information relative to each band within cluster.

Now assume that the hyperspectral data noise is white Gaussian distributed with covariance matrix$\widehat{\overline{R}}_n$. The singular value decomposition of the matrix $\widehat{R}_r$ can be written as

$$\widehat{R}_r = \overline{E_V}\overline{\sum}\overline{E_V}^T \qquad (7)$$

Suppose that $\overline{Q}_K = \overline{E}_K\overline{E}_K{}^T$ be a projection matrix onto $\overline{E}_K$, and the sample mean vector of the hyperspectral data set is calculated as

$$\vec{x}_i = \frac{1}{N}\sum_{j=1}^{N}\left(\vec{r}_j + \vec{n}_j\right) \qquad (8)$$

$$\vec{x}_i = \frac{1}{N}\overline{S}\sum_{j=1}^{N}\vec{a}_j + \frac{1}{N}\sum_{j=1}^{N}\vec{n}_j \qquad (9)$$

$$\vec{x}_i = \sum_{i=1}^{L}[\vec{e}_i + \vec{w}_i] \qquad (10)$$

where$\vec{e}$ is the data space and $\vec{w}$ is the white gussian noise. Let $\vec{e}_k$ be the projection of $\vec{e}$ onto the $\overline{E}_K$. The estimation of $\vec{e}_k$ can be obtained by projecting $\bar{x}$ onto the decomposed data space$\overline{E}_K$, i.e. $\hat{e}_k = \overline{Q}_k\vec{x}$. Since the basis set is known so the approximation of mean square error is obtained by using the bias estimation of $\hat{e}_k = \overline{Q}_k\hat{x}$. However the expected values of the basis set is equal to the basis set thus it is an unbiased estimation of basis set. So the numbers of end members are estimated as,

$$\hat{k} = \text{argmin}\left\{\varepsilon * \text{trace}\left(\overline{E_V} * \bar{\rho}_{\bar{r}_W}\right) - \left(\text{trace}\left(E[\bar{x}] * \overline{E_V} * E[\bar{x}]^T\right)\right)\right\} \qquad (11)$$

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VI. RESULTS

We used a well-known Airborne Visible/ Infrared Imaging Spectrometer [38] for our research work. The Cuprite image is used to compare and evaluate the proposed research work. It was collected by 224 spectral bands with 10 nm spectral resolutions over the Cuprite mining site, NEVADA in 1997. Cuprite is a mining area in the south of Nevada with minerals and little vegetation. The geologic summary and mineral map can be found in [39]. Cuprite has been widely used for experiments in remote sensing and has become a standard test site to compare different techniques of hyperspectral image analysis. In our research work, a sub image of size 350×350 with 224 bands of a data set taken on the AVIRIS flight. The instrument of AVIRIS covers 0.41 – 2.45 µm regions in 224 bands with a 10 nm bandwidth and flying at an altitude of 20 km, it has an instantaneous field of view (IFOV) of 20 m and views a swath over 10 km wide. Prior to the analysis of AVIRIS Cuprite image data, low SNR bands 1 – 3, 105 – 115 and 150 – 170 have been removed and the remaining 189 bands are used for experiments. Preserving the maximum information, the number of bands required are 10.

Selected bands are shown in figure 1. The Spectral Angle Mapper (SAM) computes the spectral similarity between the found spectral signatures and the laboratory spectral signatures, shown in figure 2. The smaller the spectral angle the more similar the actual and found target spectra. The values of SAM among the same minerals are lower than others. The extracted end members are predominantly of Alunite, Calcite, Kaolinite, Muscovite and Buddingtonite on selected bands are shown in figure 3. Figure 4 shows the selected bands with respect to their Centroids.Figure 5 shows clustered data and their diagonal connectivity. Figure 6 shows how the spectral angle mapper works for comparing the actual and found endmembers spectra.Figure 7 shows the correlation among the bad images and Figure 8 shows a flow chart of the algorithm.

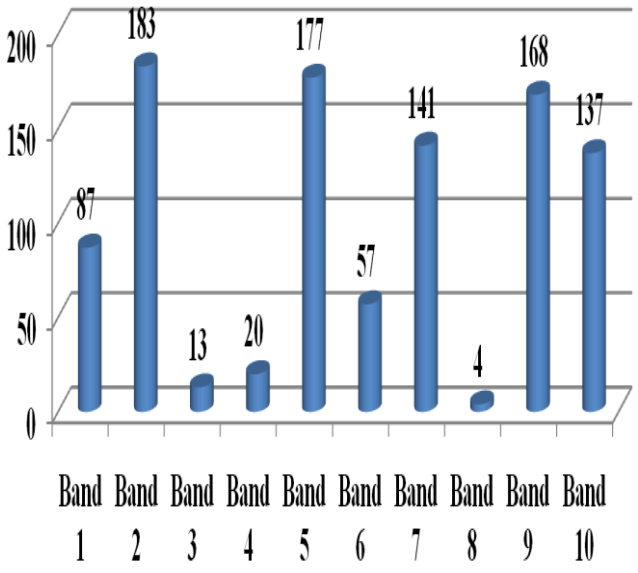

Fig. 1: Selected Bands

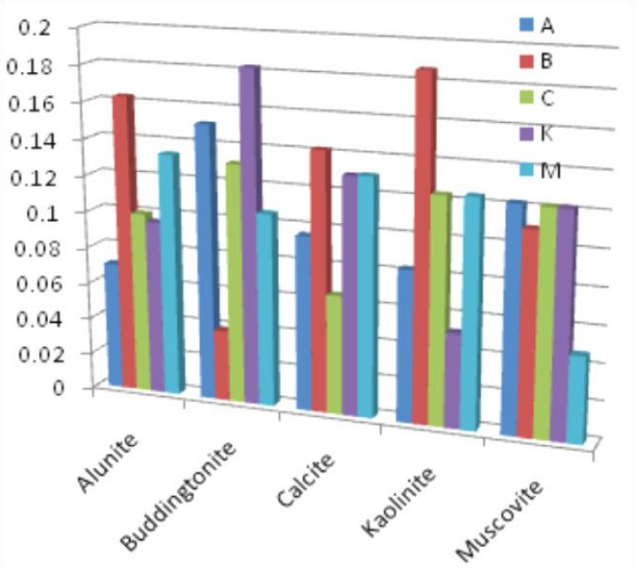

Fig. 2: Spectral Similarity of found and actual signatures

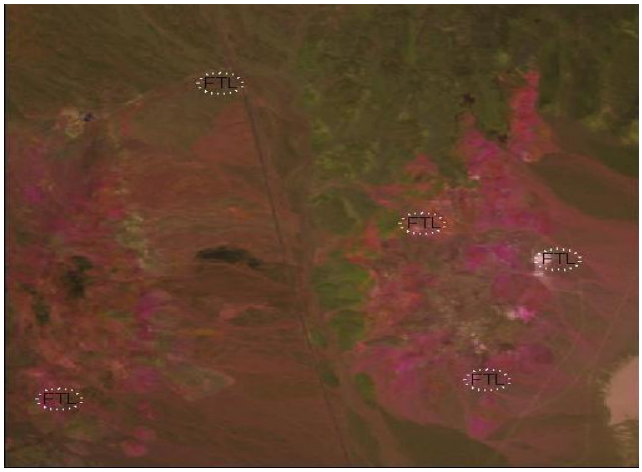

Fig. 3: End members locations

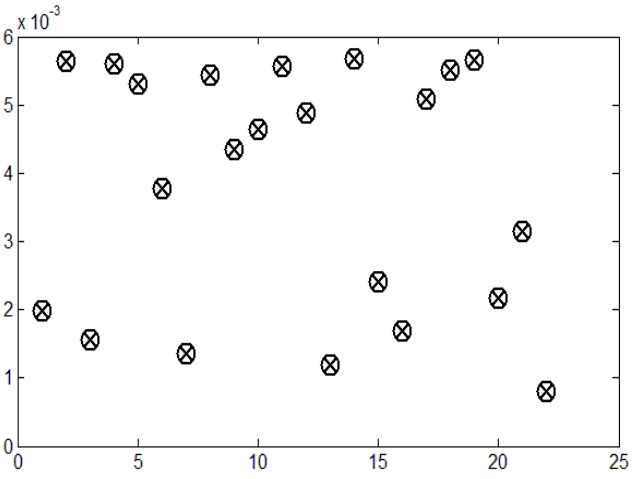

Figure 4: Selected Bands Centriods

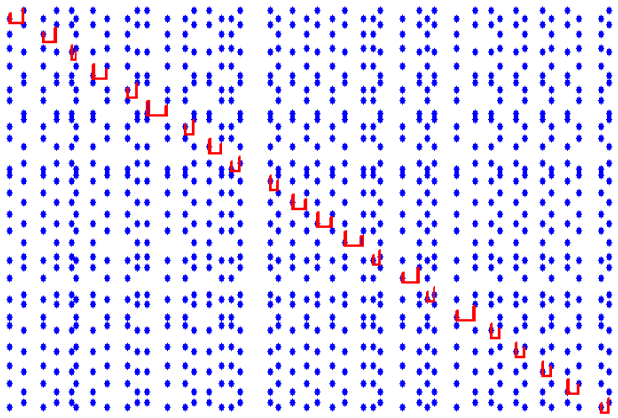

Figure 5: Data Clusters

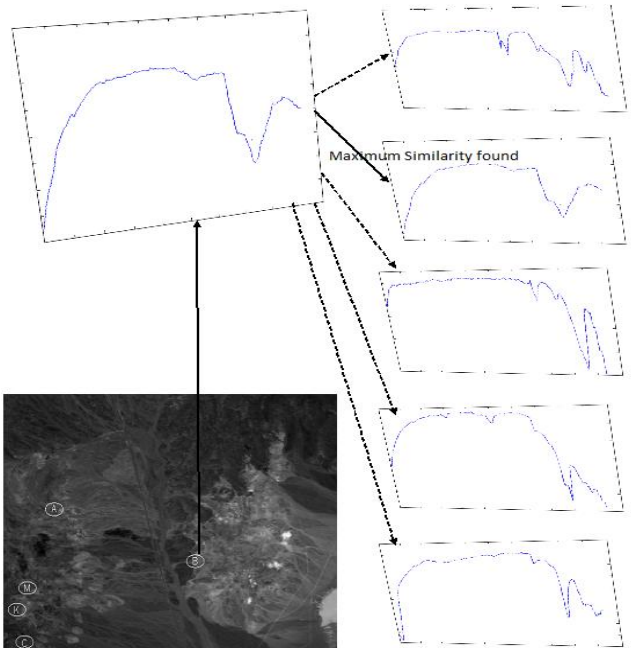

Figure 6: SAM.

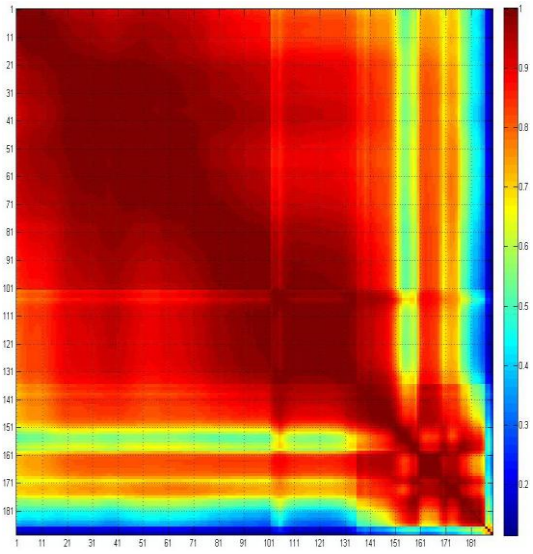

Fig 7: Correlation among the images

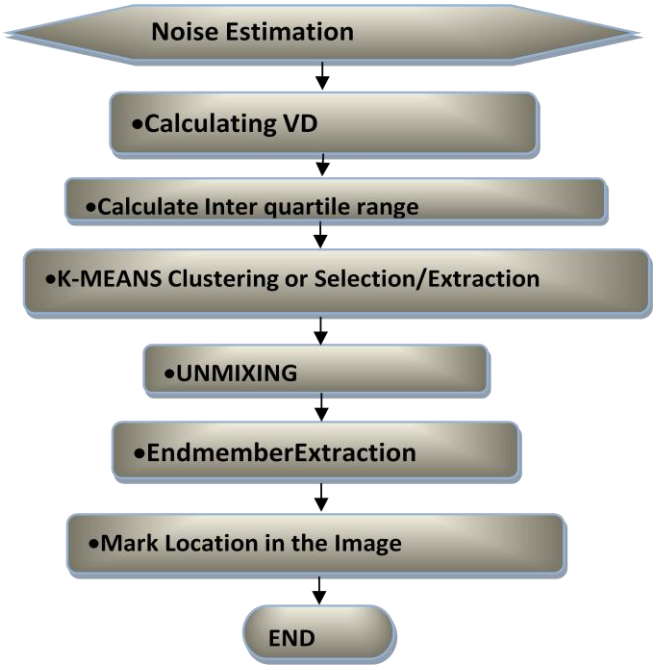

Fig 8: Flow Chart

VII. CONCLUSION

Hyperspectral data dimensional reduction and target detection objective is to estimate the number of end members and cross-pounding their abundance fractions at each pixel using the only observed data. The performance of the proposed model is illustrated with real hyperspectral data from NASA data archives. The results achieved show the effectiveness of hyperspectral data dimensional reduction and target detection on hyperspectral data. In future work, the proposed algorithm shall be improved in order to set initial parameters for band extraction.

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